The Multilingual Advantage in Language Learning: Contribution of Multilingualism and Programming Knowledge on Artificial Grammar Learning

by

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Abstract

Multilingualism allegedly makes learning new languages easier. However, in view of grammar learning, experimental results so far have been inconclusive. Moreover, multilingualism is often defined as knowledge of more than one natural language, but it is unknown how knowledge of an artificial language such as a programming language fares within this equation. We examined the effect of participants' linguistic and programming experience on their accuracy scores in an artificial grammar learning (AGL) task. Our results revealed no evidence that multilinguals were better in the AGL task than monolinguals. In contrast, participants who reported knowledge of a programming language performed significantly better than non-programmers in this task. I conclude that knowledge of a natural language and that of a programming language have different effects on cognition in view of AGL.

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Chapter 1: Introduction

Learning a new language brings many benefits to one's life, for example by providing better job opportunities (e.g., Stein-Smith, 2017), a richer social life (e.g., Jasim, 2021), healthier cognitive aging (e.g., Bialystok et al., 2007; Kroll & Dussias, 2018), and allegedly better executive functioning (e.g., Bialystok, 2007; 2011). There are many reasons to pick up a new language, but it is not easy for everyone to do so. Researchers have long been interested in the factors that make certain people better than others at learning languages. Achievements in learning a new language can be predicted by certain characteristics of the learner, for example the age of acquisition (e.g., Muñoz & Singleton, 2011), the learner's motivation (e.g., Clyne et al., 2004; Dörnyei & Skehan, 2003), or aspects of cognition as general intelligence (e.g., Cenoz & Valencia, 1994) and working memory span (e.g., Williams, 2013). Another factor claimed to predict language learning outcomes is multilingualism, such that learning a third or subsequent language is easier than learning a second (e.g., Cenoz & Valencia, 1994; Cenoz, 2003; 2013; Hirosh & Degani, 2018; Montanari, 2019; Sanz, 2000). There is support for this claim in the domains of vocabulary learning (e.g., Abu-Rabia & Sanitsky, 2010; Escudero et al., 2016; Kaushanskaya, 2012; Kaushanskaya & Marian, 2009ab; Keshavarz & Astaneh, 2004), phonology (e.g., Antoniou et al., 2015; Onishi, 2016; Wang & Saffran, 2014), and grammar (e.g., Abu-Rabia & Sanitsky, 2010; Nation & McLaughlin, 1986; Nayak et al., 1990; Cox, 2017). However, there are also several instances where such an advantage fails to be found (e.g., Edele et al., 2018; Grey et al., 2018; Lorenz et al., 2020; Del Pilar Augustin-Llach, 2019; Hopp, 2019), indicating the need for more research to be done on this topic. Specifically, there are very few laboratory studies in the domain of grammar

learning (e.g., Cox, 2017; Grey et al., 2018; Nation & McLaughlin, 1986; Nayak et al., 1990). There are several limitations to these studies, including small sample sizes and differences in methodologies which do not allow to draw a strong conclusion about their results. Nayak et al. (1990) found multilingual participants to outperform monolinguals in learning an artificial grammar following rule-discovery, or explicit-inductive instructions. However, this study had some limitations, including few participants in each group (n = 12), and an artificial grammar that did not rely on rules similar to those found in natural languages. Thus, it remains to be explored whether the multilingual advantage in artificial grammar learning will be observed when (a) a sufficiently large sample size is obtained and (b) when the artificial grammar is based on rules that are similar to rules found in natural languages. The first goal of my thesis research is to test the effect of multilingualism on artificial grammar learning. Consistent with prior research (e.g., Nayak et al., 1990), I predict that individuals speaking multiple languages will achieve higher proficiency in a grammaticality judgement task after a short explicit-inductive learning session of an artificial grammar compared to monolingual individuals.

Further, to date there has been no exploration of how knowledge of another artificial language affects subsequent language learning. Multilingualism is often defined as knowledge of more than one natural language, but it is unknown how knowledge of an artificial language, such as a programming language, fares within this equation. Researchers have recently been interested in whether programming languages are processed similarly to natural languages (e.g., Fedorenko et al., 2019; Graafsma, 2021). There is no research to date testing how knowledge of a programming language compares to that of another natural language in view of non-native grammar learning. The current

study aims to fill this gap. Specifically, the second goal is to explore the effect of knowing an artificial (programming) language on artificial grammar learning, and whether this effect is similar to those associated with multilingualism. I predict that since programming involves manipulating symbolic rule-based systems similar to those used in artificial grammar learning tasks, (and similar to ones used in natural languages), individuals who know a programming language will achieve higher proficiency than non-programmer individuals in an artificial grammar learning task following the instruction to look for the rules underlying the structure of the stimuli.

1.1 The Multilingual Advantage in Language Learning

It is often claimed that multilinguals are better than monolinguals at learning new languages (e.g., Cenoz & Valencia, 1994; Cenoz, 2003; 2013; Hirosh & Degani, 2018; Montanari, 2019; Sanz, 2000). For example, studies have found that multilingual learners outperform monolingual learners in acquiring novel words (e.g., Abu-Rabia & Sanitsky, 2010; Escudero et al., 2016; Kaushanskaya, 2012; Kaushanskaya & Marian, 2009ab; Keshavarz & Astaneh, 2004), new phonological contrasts (e.g., Antoniou et al., 2015; Onishi, 2016; Wang & Saffran, 2014), and grammatical knowledge (e.g., Abu-Rabia & Sanitsky, 2010; Nation & McLaughlin, 1986; Nayak et al., 1990; Cox, 2017). Moreover, multilingualism remains a significant predictor of language learning outcomes after controlling for individual differences such as age, motivation, exposure, or general intelligence (e.g., Cenoz & Valencia, 1994; Sanz, 2000), such that this advantage would be linked to multilingualism rather than to an individual predisposition of multilinguals to be better language learners.

There are several potential sources for the multilingual advantage in language learning. A basic difference between monolinguals and multilinguals is in the number of different languages that they know. Multilinguals may be advantaged in learning new languages because they have access to larger linguistic repertoires than monolinguals (e.g., Cenoz, 2003), which augments the possibility to encounter familiar linguistic features in a new language. For example, shared etymology or phonological similarities with the target language makes it easier to remember new words (e.g., Brohy, 2001; Clyne et al., 2004; Kaushanskaya et al., 2013), identify morphological paradigms (e.g., Clyne et al., 2004), or acquire new phonological contrasts (e.g., Antoniou et al., 2015; Wang & Saffran, 2014). Linguistic proximity between the languages one knows, and a target language reduces the load of new information to be assimilated. The observation of a multilingual advantage in foreign language learning has sometimes been attributed to the existence of such linguistic proximity between known and target languages (e.g., Brohy, 2001), or the lack of one (e.g., Del Pilar Agustín-Llach, 2019). In this view, the benefit of prior linguistic knowledge is limited to specific cases where there are shared linguistic elements between known languages and the target. Moreover, this explanation predicts that monolinguals could be advantaged in the case where their mother tongue bore more similarities with the target language than that of the compared multilingual group. Alternatively, it also predicts no group differences in the case where neither the monolingual nor multilingual learners have knowledge of a language similar to the target language. Both scenarios were tested by Wang & Saffran (2014) and the multilingual participants were found to outperform the monolinguals even when the multilingual group had reduced transfer potentials, and even when compared to a monolingual group

who had increased transfer potential. Overall, this study showed that multilingualism was a better predictor of language learning achievements than linguistic proximity. Several other studies attest a multilingual advantage in cases where opportunities for transfer are mitigated (e.g., Antoniou et al., 2015; Clyne et al., 2004; Kaushanskaya & Marian, 2009b). Therefore, although prior linguistic experience can sometimes provide specific advantages through transfer, this situation does not tell the whole story for why multilinguals generally outperform monolinguals in learning new languages.

In fact, there are cases where prior linguistic knowledge can be detrimental to learning new linguistic elements. When presented with an item that has phonological, orthographic, or semantic overlap across different languages known by a multilingual, there is parallel activation of the item and its counterpart (e.g., Blumenfeld & Marian, 2013; Jouravlev et al., 2014; Jouravlev & Jared, 2014; 2018; Van Heuven et al., 2008). This may be useful to learn cognates. Otherwise, prior knowledge interferes with learning novel items, and must be repressed. Doing so is called cross-linguistic interference management and is something multilinguals often have more practice with than monolinguals. Being multilingual involves more than knowing many languages. It also implies managing these languages in one's head. Although multilinguals can usually easily alternate from one language to another, in their mind, no language is ever totally turned off (e.g., Van Heuven et al., 2008). Multilinguals, especially more balanced multilinguals (e.g., Blumenfeld & Marian, 2013), are better at overcoming this interference than monolinguals (e.g., Kaushanskaya & Marian, 2009a). Therefore, a multilingual lifestyle, or frequent use of more than one language involves more practice

in managing multiple codes in one's mind. This skill may become useful for departing from one's expectations regarding known languages' patterns.

In turn, managing a large linguistic repertoire and linguistic competition can lead to develop better expectations about the patterns that can be found in languages in general. Jessner (2008) theorizes that this competition provides an ideal context to compare languages and identify the differences and similarities among them, which leads one to become more aware of how languages work. The multilingual advantage in language learning is often attributed to greater metalinguistic awareness (e.g., Bialystok, 1988; 2001; Clyne et al., 2004; Dillon, 2009; Jessner, 1999). The benefits of metalinguistic awareness in novel language learning may manifest themselves as more ease in identifying syntactic constituents (e.g., Clyne et al., 2004), abstract meaning from syntax (e.g., Bialystok, 1988), or better intuitions when guessing meanings of unknown words from context (e.g., Clyne et al., 2004; Gibson & Hufeisen, 2003). Therefore, several language learning strategies used by multilinguals can be linked to their greater metalinguistic awareness. Dillon (2009) explains that metalinguistic awareness can orient language learners towards using more appropriate learning strategies by providing them with a better ability to build expectations about the rules of the target language. Metalinguistic knowledge consists of linguistic generalizations that hold beyond the linguistic corpus one is familiar with. Jessner (2008) defines metalinguistic awareness as knowledge about languages built from applying meta-cognitive processes onto one's own linguistic knowledge. Therefore, while developing their metalinguistic awareness, multilingual individuals acquire more general strategies for reflecting about languages, which makes it easier for them to break down new languages.

In fact, many cognitive impacts of multilingualism can be observed through multilinguals' language learning patterns. Studies have noted that multilingual learners use a larger number and wider variety of language learning strategies than monolinguals (e.g., Grenfell & Harris, 2015; Qasimnejad & Hemmati, 2014), and are more likely to adapt these strategies in view of task instructions (e.g., Nayak et al., 1990). In this later study, multilingual participants used more mnemonic strategies, such as making associations between a word and a shape, than monolinguals when asked to remember the stimuli they were presented with. When participants were told to identify the rules underlying the stimuli, the multilingual participants used more linguistic strategies, such as replacing the letter strings by verbs or nouns familiar to them. Dmitrenko (2017) found that monolingual and multilingual learners differ most in view of cognitive strategies, such as establishing relationships between languages that are alike, metacognitive strategies, as in learning how to make efficient transfers, and social strategies, for example maximizing opportunities to practice with peers. Other studies note important differences in affective strategies, such that multilingual learners are more willing to be corrected (e.g., Clyne et al., 2004), and feel less panic when faced with unknown words (e.g., Grenfell & Harris, 2015). Therefore, multilinguals and monolinguals learn new languages is different ways. Importantly, these differences in learning strategies can reflect further differences in cognition.

Finally, some have argued that the patterns of learning strategies employed by multilingual learners reflect a more automatic parsing of the target language's structure, which leaves more cognitive resources for consciously identifying the grammatical rules of the target language (Nation & McLaughlin, 1986; Nayak et al., 1990). It is therefore

possible that multilinguals also benefit from an enhanced unconscious ability to track patterns in the structure of linguistic inputs. This ability is sometimes referred to as statistical learning ability. Researchers have found that multilingual participants perform better on statistical learning tasks than monolingual participants (e.g., Potter et al., 2017; Wang & Saffran, 2014), with an additional advantage for balanced multilinguals (e.g., Bartolotti et al., 2011; Onnis et al., 2017). The explanation given by Onnis et al. (2017) is that tracking multiple linguistic inputs daily makes one more sensitive to statistical regularities in language. However, there are also studies that failed to find an advantage for multilingual individuals over monolinguals in non-linguistic statistical learning tasks (e.g., Poepsel & Weiss, 2016; Yim & Rudoy, 2013), or found such an advantage but only when tasks were done in the auditory modality (e.g., Potter et al., 2017). Therefore, these enhanced abilities of multilingual individuals to unconsciously identify patterns may be restricted to the linguistic domains. Nonetheless, these studies show that multilingualism potentially provides an advantage in the automatic parsing of linguistic input.

The discussion so far shows that many of the proposed sources for the multilingual advantage involve cognitive changes brought by the frequent use of more than one language. An important factor is how this knowledge interacts in the multilinguals' mind. Overall, there are multiple indications that the source of the multilingual advantage is not merely knowledge of more than one language, but the co-habitation and interaction of these languages in the mind. These interactions are multiplied in the case of daily usage of more than one language, and studies find a positive relation between the daily amount of language switching and success in learning new languages (e.g., Maluch & Kempert, 2017; Keshavarz & Astaneh, 2004; Stocco &

Prat, 2014). Moreover, linguistic proficiency and usage among multilinguals has found to modulate levels of metalinguistic awareness (Bialystok, 1988; Sanz, 2019; Woll, 2017), the amount and variety of learning strategies used (Kemp, 2001; Dmitrenko, 2017), the ability to manage linguistic interference (e.g., Blumenfeld & Marian, 2013; Lorenz & Siemund, 2020), and to detect statistical regularities in the input (e.g., Bartolotti et al., 2011; Onnis et al., 2017). In this perspective, the multilingual advantage would be grounded in cognition and intimately connected to a multilingual's linguistic habits.

Alternatively, it is also possible that multilinguals draw many benefits from their social setting. The availability of a multilingual community outside of the classroom can be beneficial to learners (e.g., Brohy, 2001; Clyne et al., 2004), either by providing more opportunities to practice, providing direct feedback, or normalizing making mistakes, which contributes to building learners' self-confidence. As mentioned earlier, one of the major differences between monolingual and multilingual learners in their learning strategies was multilinguals' resort to more practice with peers (Dmitrenko, 2017). Arguably, this strategy is useful only if the learner has access to people with whom to practice, or a community that supports such practice. Studies done in natural settings that report an advantage of multilingual students over their monolingual peers are often found in contexts where the minority languages have institutional support, for example in Spain (e.g., Cenoz & Valencia, 1994; Sanz, 2000), Australia (e.g., Clyne et al., 2004), or Canada (e.g., Mady, 2017; Swain et al., 1990). Comparatively, it is not rare to observe no significant group difference in the case of multilingual students whose L1 is a minority language that does not benefit from institutional support (e.g., Cenoz, 2003; Lorenz et al., 2020), or in cases where multilingual learners do not have a good grasp of the majority

language (e.g., Hopp, 2019), which is often the language of instruction. A positive attitude towards multilingualism at the institutional level may be a key factor for the multilingual advantage to be observed (Cenoz & Valencia, 1994; Sanz, 2000). In this view, the multilingual advantage is not only rooted in cognition, but also strongly depends on social factors.

Overall, although there are many studies that support the existence of a multilingual advantage in language learning, there are also several instances in the literature that cast doubts upon the universality of this phenomenon. For example, as mentioned in the paragraph above, it is less likely to find evidence for this advantage among certain groups of multilinguals, as in the case of heritage speakers (e.g., Hopp, 2019; Lorenz et al., 2020; Lorenz & Siemund, 2020), or multilinguals issued from immigration (e.g., Edele et al., 2018). On the other hand, this advantage is often reported as more salient for multilingual populations who are more balanced in terms of proficiency and use in at least two languages (e.g., Maluch & Kempert, 2017; Keshavarz & Astaneh, 2004; Stocco & Prat, 2014). Moreover, we can also question whether this advantage holds in all domains of language learning. For example, no advantage for multilingual learners over monolinguals is found in the case of phonological contrasts that are deemed universally "harder" to acquire (Antoniou et al., 2015). In the domain of grammar learning, there are instances where no advantage at all is found (e.g., Grey et al., 2018). Finally, there are studies that looked at similar participants and contexts that fail to replicate the same results in view of a multilingual advantage in language learning (e.g., Cenoz & Valencia, 1994; Del Pilar Augustin-Llach, 2019). These examples highlight the

need for more research to be conducted about the potential multilingual advantage in language learning.

Studies done in natural contexts may involve many confounding variables due to social dynamics (e.g., Cenoz, 2008; Montanari, 2019). Although student cohorts learning a mandatory foreign language allow for an easy access to large pools of participants, they do not allow for a good control of contextual variables that can affect the outcome of language learning beyond cognitive aspects of multilingualism. Laboratory research is extremely valuable in this view to confirm and expand upon the results obtained by studies done in natural settings. Research done in a laboratory allows to test for language learning abilities more generally, while ensuring that the different groups have the same amount of familiarity with the target language (preferably, none), and receive a similar amount of practice. Such experimental support has been provided in the lexical domain, for vocabulary learning (e.g., Escudero et al., 2016; Kaushanskaya, 2012; Kaushanskaya & Marian, 2009ab) and phonological awareness (e.g., Antoniou et al., 2015; Wang & Saffran, 2014). However, advances on the question of grammar learning have been lagging. At least four studies have compared monolingual and multilingual learners' performances in grammar learning (e.g., Cox, 2017; Grey et al., 2018; Nation & McLaughlin, 1986; Nayak et al., 1990), but their results have been mixed and differences in their methodologies do not allow for a clear parallel among them. The following section will outline the major aspects of these studies and their contributions to the topic of the multilingual advantage in grammar learning.

1.2 Experimental research on the multilingual advantage in grammar learning

Artificial languages are useful to test various aspects of languages learning in a laboratory setting (e.g., Ettlinger et al., 2016; Sanz & Cox, 2017). Artificial grammars usually rely on a few rules and a small vocabulary, so they can be learned quickly and with high accuracy. In these experiments, participants usually first go through a period of familiarization with the artificial language, which may involve some form of practice. Then, participants' learning is assessed through a two-alternative forced choice task. For studies interested in grammar learning, this task is a grammaticality judgement task. Task instructions can be adapted to trigger different types of learning. Using Dekeyser (2003)'s terminology, when learners are given instructions about the rules of a grammar, the learning is deductive and explicit, when learners are instructed to find rules on their own, the learning is inductive and explicit. Learning without awareness as in the case of first language acquisition would be implicit and inductive. Experiments that aim to elicit this type of learning vary in regards of their task instructions. In some versions, participants are instructed to pay attention to the stimuli (e.g., Nation & McLaughlin, 1986), in others, they are instructed to memorize the stimuli (e.g., Nayak et al., 1990). Artificial language paradigms have been used to investigate the multilingual advantage in language learning in different fields, such as those of second language acquisition and cognitive psychology, which lead to sometimes non-overlapping use of the terms 'explicit' and 'implicit' (Sanz & Cox, 2017). To limit confusion, tasks conditions will be discussed here using the terminology defined by Dekeyser (2003), as outlined above.

The first study to compare the effect of prior language learning experience on subsequent grammar learning in a laboratory setting was that of Nation & McLaughlin

(1986). Their investigation came from an information processing perspective, and they hypothesized that more expertise in learning languages leads to better abilities to learn new languages. In this view, multilingual individuals would be 'language learning experts' who are expected to perform better than bilinguals who are less experienced language learners. Bilinguals, in their turn, should perform better than monolinguals. The stimuli used in this study were strings of 3 to 6 consonants generated by a finite-state grammar. There were three groups of participants (n = 14 in each group) that varied in terms of whether participants were fluent in one (monolingual), two (bilingual), or over four languages (multilingual). Each group first participated in an implicit-inductive learning condition and then, around ten days later, in an explicit-inductive learning condition. In the implicit learning condition, participants were only told to pay attention to the stimuli without further instruction or mention of rules in the stimuli. In the explicit learning condition, participants were informed that the stimuli obeyed certain rules and that their task was to figure out these rules. Each condition first included a familiarization phase where participants were shown 20 examples of grammatical stimuli. In the implicit condition, the stimuli were shown one by one for 7 seconds three times each. For the explicit condition, the stimuli were printed on a sheet of paper which participants were given 7 minutes to study. In each case, the grammaticality judgement task (i.e., decide whether a sentence is grammatical) contained 50 different stimuli, half of which were incorrect, presented twice for a duration of 7 seconds. Participants were presented with a different, but comparable grammar for each condition. The results revealed a significant group difference in favor of the multilingual group in the implicit condition only. Compared to monolinguals and bilinguals, multilingual participants also had a lesser

tendency to mis-classify the same stimuli twice in the grammaticality judgement task for the implicit condition. However, these results were not replicated in the explicit learning condition, where the three groups (i.e., monolingual, bilingual, and multilingual) performed similarly.

Although Nation & McLaughlin (1986) concluded that multilingual participants have an advantage in grammar learning under implicit learning conditions, several limitations of this study cast doubts on this conclusion. For example, due to the conditions' ordering, and the different modes of familiarization in each condition (being shown each item one by one vs. studying a list), it is unclear whether the task instruction is the only variable influencing the results. Another limitation concerns the stimuli used, strings of consonants, which questions whether the results can be generalized to natural language. Words or morphemes in natural languages are composed of syllables rather than single consonants and are arranged in a hierarchical rather than sequential manner. Moreover, although the study found that the multilingual group performed better than the bilingual group, it is unclear that this difference reflects only an effect of the number of languages known since the bilingual and multilingual groups also differed in terms of age of acquisition. Namely, the bilingual group included only people who had learned a second language before the age of twelve, whereas everyone in the multilingual group had learned at least one language as an adult. Further, the sample size was very limited with only 14 participants per group. Overall, there are several limitations to this study that preclude us from making a conclusion that knowledge of multiple languages contributes to further advantage in grammar learning.

Nayak et al. (1990) followed up on Nation & McLaughlin (1986) with several modifications to the original methodology. The stimuli were sentences composed of 2 to 5 items shaped as CVC syllables. These sentences obeyed a structure more like that of natural languages than the stimuli used by Nation & McLaughlin in that they were decomposable into phrases and words organized in a hierarchical manner. Each word was also mapped to a specific colored shape and each participant was placed in only one of the two learning conditions. Changes were also made to the groups and the conditions' instructions. There were two groups, a group of monolinguals (n = 24), and a group of multilinguals (n = 24), who reported equal proficiency in three or more languages and had learned at least one language after the age of twelve. To induce implicit-inductive learning, Nayak et al. (1990) employ a 'memory' condition where participants are instructed to do their best to remember the stimuli. The other condition, called a 'rule-discovery' condition, promotes explicit-inductive learning, and includes similar task instructions as the explicit condition in Nation & McLaughlin (1986). Both are explicit-inductive learning conditions, where participants are instructed that the stimuli they will be presented with obey rules and that they should do their best to identify these rules. For the learning phase, participants saw 40 different grammatical sentences three times each for a duration of 5 seconds each, one at a time on a computer screen. Another important difference in this study is that the learning phase was interrupted on three occasions to inquire about participants' learning strategies. At these times, participants were asked to record instructions to help future learners in this task. Participants were tested on their learning of grammar rules through a grammatical judgement task. For this task,

participants were presented with 48 new sentences, built from the same words and grammar as in the learning phase, but there was no visual referent.

The multilingual group obtained significantly higher accuracy results than the monolingual group in the explicit-inductive, or rule-discovery task, but there were no such differences in the implicit-inductive, or memory task. These results are opposed to those found by Nation & McLaughlin where the multilingual group performed equally under both conditions. However, since the two studies employed different task instructions for the implicit-inductive task, and different grammars as the object of learning, it is unclear that the results reflect the same processes. Moreover, although this artificial language was designed to look more like a natural language, it was also made to avoid rules that are found in natural languages of the world. The authors took this care to avoid any potential implication of transfer. However, doing so also potentially impedes the generalizability of the results to natural language contexts. Again, we can also note that those results rest upon the inclusion of a very small sample size per group (n = 12). Notwithstanding these limitations, the main take away from this study was finding a multilingual advantage in artificial grammar learning under explicit-inductive condition. This brings a new light on the results obtained by Nation & McLaughlin in this condition, which were obscured by the potential effect of task ordering.

Cox (2017) extended the question of the multilingual advantage in language learning to an older population. Participants (n = 45) aged 60 and over learned a miniature version of Latin. The study included a native English monolingual group and a multilingual group where participants all reported using both English and Spanish on a regular basis. Participants were further divided under two experimental conditions. One

was an ‘instructed’ condition that would target explicit-deductive learning. This condition involved a grammar lesson of Latin morphosyntax pre-practice. This lesson was intended to provide the kind of information one would receive in a foreign language classroom. It included basic grammar knowledge such as an explanation of what grammatical categories are, English-Latin translations, and English vs. Latin grammar comparisons. The aim of this formal instruction was to promote metalinguistic awareness and transfer by explicitly instructing participants how the new information relates to their existing knowledge. For the non-instructed condition, participants only saw correct instances of Latin sentences, but this familiarization period was made to be as long as that of the instructed condition so that participants in each conditions received comparable amount of exposure to the target language. The non-instructed condition involves a similar kind of learning as that found in explicit-inductive conditions in earlier studies. Participants were tested on aural interpretation, written interpretation, and grammaticality judgement at three time-points. The first series of tests was administered during the first meeting, then participants came back two more times following a one-week, and then a two-week interval.

The study reports significant group differences in the grammaticality judgement task between the monolingual group in the no instruction condition, and the multilingual group in the instructed condition immediately following practice. However, since the difference is only significant across groups that participated under different learning conditions, it is clear that the results are due only to the linguistic status. Moreover, because of the possible interplay between working memory abilities and older age, it is unclear that these results can be generalized to younger populations. An additional

limitation of this study is the use of a miniature version of a natural language as the object of learning. Doing so straightforwardly counters the potential downfalls associated with using an artificial language as the two previous studies discussed here, such that these grammars did not obey rules found in natural languages of the world. However, using Latin brings in the exact situation that those studies wanted to avoid by using an artificial grammar, namely the potential for transfer to blur learning achievements. The importance of transfer issues is well illustrated by the number of participants who had to be excluded in Cox (2017) because they scored above 67% on Latin pre-test (n = 11). Moreover, although Latin is considered a dead language, its influence on other languages, either historically or etymologically, as well as its general popularity in mainstream culture makes it doubtful that what participants learned in the experiment was entirely novel, or at least that it was equally novel among participants. Overall, although this study is a good contribution for the inclusion of older participants in language learning research, it does not provide much evidence about the claim of a multilingual advantage in language learning.

Finally, Grey et al. (2018) compared a group of English monolingual participants (n = 17) and a group of early balanced Mandarin L1 - English L2 multilinguals (n = 16) on their learning of Brocanto2, a version of the artificial language Brocanto. Brocanto and its derivations are composed of rules found in natural languages and have the power to elicit patterns of brain activity that are similar to those elicited by natural languages (e.g., Friederici et al., 2002; Morgan-Short et al., 2012). For this experiment, there was only one task condition, similar to the 'instructed', or explicit-deductive condition in Cox (2017). Participants were given explicit instructions prior practice and received

metalinguistic feedback about the grammar of Brocanto2 during practice. In this experiment, the grammaticality judgement task was paired with electroencephalography recording. The grammaticality judgement task with electroencephalography was given at two time-points during the experiment, when participants reached low-proficiency in the target language, and when they reached high-proficiency. Participants were first given a vocabulary lesson about the words of Brocanto2, then they completed blocks of comprehension and production training until they reached a certain level of accuracy. For comprehension blocks participants had to identify the proper board game configuration described by a given sentence. For production blocks, participants had to produce the game move associated with a given sentence. Participants practiced on these blocks until they obtained at least 45% accuracy on two consecutive blocks. This was marked as the low proficiency stage, at which point participants completed their first round of a grammaticality judgement task with electroencephalography. After this, participants kept practicing until they reached above 95% accuracy on two consecutive blocks, or until they completed all 44 available practice blocks. At this point, participants were deemed to have reached a high proficiency level and completed a second round of a grammatical judgement task paired with electroencephalographic recording.

The recordings of participants' brain activation patterns show marked group differences at both the low-proficiency and the high-proficiency testing points. There was also a trend for multilingual participants to reach the low proficiency level faster, or in less blocks, than monolingual participants. However, there were no significant differences on accuracy measures for the grammaticality judgement task. It is hard to compare the grammaticality judgement task results to those obtained in previous studies

because the learning condition is different than those employed by Nation & McLaughlin (1986) and Nayak et al. (1990), and the participants are younger than those in Cox (2017). Therefore, although this study provides evidence for different underlying processes in monolingual and multilingual learners, the results from the grammaticality judgement task do not corroborate that these underlying processes lead to significantly better performances on artificial grammar learning.

Overall, it is hard to trace the exact source for the mixed results in these studies since they each differ from each other in some, often non-compatible, methodological respects. The stimuli, learning condition, participants' linguistic background, or age, may all play an important role in modulating the results. For example, different learning conditions are associated with different brain activation patterns. Morgan-Short et al. (2012) showed that explicit learning with or without metalinguistic instruction modulates different ERP patterns in participants learning an artificial grammar, namely that those in the non-instructed version had more native language-like patterns.

The condition that comes up the most among the studies reviewed in this section is the explicit-inductive learning condition (e.g., Cox, 2017; Nation & McLaughlin, 1986; Nayak et al., 1990) and evidence for a multilingual advantage in this condition was found in at least one of these studies (e.g., Nayak et al., 1990). However, each of these studies also employed a target language that is potentially problematic either in view of ecological validity (e.g., Nation & McLaughlin, 1986; Nayak et al., 1990), or transfer (e.g., Cox, 2017). Although Grey et al., (2018) counter these issues by using the ecologically valid artificial language Brocanto, it is not possible to make a direct parallel with earlier studies because of the different task condition employed. In view of this and

the general limitation of small sample size across each of these studies, it remains to be discovered whether the multilingual advantage found by Nayak et al. (1990) will hold using a large sample size and an artificial grammar that follows rules like those found in natural languages of the world.

This overview of the methodologies brings in further questioning about the cognitive processes involved in acquiring and using artificial languages. If artificial language paradigms are good alternatives to test aspects of natural language learning in a laboratory setting, it can be asked whether artificial languages acquired in a real-life setting are also potentially equivalent to natural languages in cognition. Multilingualism has been defined earlier as knowledge of more than one language, and I discussed how an important source of the multilingual advantage seems to be the daily interaction of more than one language in one's mind. In this view, it is interesting to inquire how knowledge of an artificial language such as a programming language fares within the multilingualism equation.

1.3 Programming Languages vs. Natural Languages: Similarities and Differences

In its basic definition, a language is a system of arbitrary symbols and rules to combine these symbols with the goal of communicating. Any language (natural or artificial), such as Python, English, or Brocanto, fulfills these requirements. It is an open question, however, whether these languages are equivalent in cognition. Researchers working on programming education and programming cognition have recently begun to address this question. Computers are some of the most useful tools available today, making programming an essential skill. The growing need for efficient programmers and the implementation of mandatory programming courses at the K-12 level have created an

incentive to reform programming education, a subject where students are often reported to struggle (e.g., Jenkins, 2002; Portnoff, 2018), and where teachers have had little guidance (e.g., Szabo et al., 2019). One proposed approach in this direction has been to teach coding as a foreign language (e.g., Bers, 2019; Pandža, 2016; Portnoff, 2018), where learning a programming language is defined as learning a symbolic rule-based system, similar to learning another language. For teaching programming at a young age, this approach means familiarizing learners with programs' organization and programming software' interface before teaching how to write and read code, similar to how literacy is developed in the case of natural language (e.g., Bers, 2019). For older learners, it may involve guiding learners towards making positive transfers from their natural language knowledge when it is possible to do so, for example in the case of cognates (e.g., Pandža, 2016), or provide exposure to well-written code that mimics immersive learning (e.g., Portnoff, 2018). So far, these initiatives have been claimed to be beneficial to novice learners of programming.

The main motivation for the view that programming and natural languages may be learned and processed similarly revolves around their basic composition. Both code and natural language are built from similar elements, such as a limited set of abstract symbols, a limited set of rules, and an inventory of form-meaning mappings; a vocabulary (e.g., Bers, 2019; Pandža, 2016; Fedorenko et al., 2019). Together, these basic elements can be used to productively derive an unlimited number of meaningful sequences of symbols, some never encountered before by the user. The popularity of the initiative to teach code as a second language coupled with the little that we know about programming cognition has created a need for more empirical evidence about the

potential overlaps between the cognitive mechanisms that support programming and natural languages. Fedorenko et al. (2019) proposed a framework that formalizes the parallels between programming and natural language processing, which provides a theoretical basis for such an investigation to take place. In this framework, both programming and natural language are defined as systems that manipulate symbolic representations according to rules. In these systems, symbols are recursively combined into units of increasing complexity. In natural languages, these complex units can be words, sentences, or texts, and they have equivalents in code, namely, functions, code lines, and programs. In both cases, these units encode information that can be decoded by other users of the system. Therefore, a major parallel between natural and programming languages that warrants investigating whether they are processed similarly is that they both involve a syntactic and a semantic component, or meaningful and structured representations.

Some examples of how syntax and semantics operate in code similar to natural language can be given in view of the concepts of category-selection, semantic-selection, and argument structure. Respectively, these concepts refer to how items in a language require to combine with other items of a specific grammatical category, that bears specific semantics, and the correct amount of such items. In both code and natural languages, the different items in a sequence of items, such as a sentence or a code line, bear specific roles. For example, nouns and variables refer to certain entities, whereas verbs and functions imply certain actions to be performed onto or by these entities. These roles or categories also dictate how items combine with one another. The concept of category-selection in linguistics explains that some items require to combine with items

of a specific category. For example, a verb like *drive* requires a noun phrase as a subject. Similarly, a function like *print()* requires a variable as an object. Failure to combine with an item of the appropriate category creates a crash in both derivations. For example, the sentence **eat drive* is not well-formed and cannot be parsed. In coding, the same is true for a line as **print(sum()).* These restrictions also apply to the content or meaning of items in each case. In linguistics this is called semantic-selection and refers to the situation where an item requires to combine with other items that bear certain meanings. For example, in English, the verb *drive* requires that its subject be a volitional agent. A similar case in Python may be a function like *append* which requires its object to be a list. If these requirements are not fulfilled, meaning cannot be computed. Errors of the like do not only happen in cases where items are combined with the wrong items but can also arise if there are too many or too little items. The argument structure of an element dictates how many elements are required, and how many optional elements can be added. For example, the verb *drive* requires one noun phrase as a subject, and optionally one noun phrase as a direct object and an optional prepositional phrase as an indirect object. In a programming language like Python, the function *append* requires two variables. Overall, there are strict syntactic and semantic rules that dictate which items can combine, and how they combine in both natural and programming languages.

At a glance, programming languages may look quite different from natural languages. For example, the use of parentheses, punctuation, and indentation is more frequent and widespread in code than in natural language. These symbols occur in almost every line as they often have a role similar to that of a morphological or structural marker between the different elements. Moreover, because of the nature of the operations

performed using programming, code may more frequently involve numbers. However, moving beyond this, we can notice that many aspects of code are directly taken from natural language, or involve using natural language constructions, in many cases English. In these cases, we can notice a certain interplay between programming and natural language knowledge. For example, the names of functions and variables in code are often based on English words or English abbreviations, and keywords are often cognates of English words (e.g., Fedorenko et al., 2019; Pandža, 2016). English identifiers, especially if there is overlap in meaning, facilitates learning for English speakers (e.g., Guo, 2018; Stefik & Siebert, 2013; Fedorenko et al., 2019). In this case, code learners who know English can parse these items directly from their knowledge of English. However, as for prior linguistic knowledge interference that can occur when learning a new natural language, students generally struggle more when learning items that overlap with English in form but not in meaning, such as is often the case for the keyword "while" (Bonar & Soloway, 1983). Another case where prior natural language knowledge interferes with learning programming has to do with reading habits. Novice programmers tend to read code the way one would a text, in a linear manner, rather than back and forth as an expert programmer would (Busjahn et al., 2015). It is a basic reflex for novice programmers to approach code as they would a natural language. Moreover, as noted by Fedorenko et al. (2019), programs do not only contain source code lines, but many comments that are entirely written in natural language. Therefore, parsing a program necessarily involves natural language processing in view of identifiers and comments.

Natural language experience possibly also has a more general impact on learning code. Prat et al., (2020) found that language aptitudes, as measured by the Modern

Language Aptitude Test, were a significant predictor of success in learning the programming language Python. However, studies that compared the effect of taking a foreign language course on achievements in a programming course, or vice-versa, do not find such straightforward association between language learning aptitudes and programming aptitudes. For example, Byrne & Lyons (2001) found no significant differences on grades obtained in foreign language courses between students who were enrolled in a programming course and those who were not. On the other hand, Agarwal et al. (2021) found that having taken a foreign language course did not predict better achievements in a programming course. Although the results obtained in these two studies may come across as contradicting those obtained by Prat et al. (2020), it is not clear that grades are a good measure of one's language learning abilities as a variety of skills are being assessed in native and foreign language courses that are unrelated to successful language learning (e.g., book report, debating, critical analysis). For example, another study that looked at the effect of programming knowledge on cognition found a strong association between this knowledge and better performance on tasks that required creative thinking, mathematical skills, metacognition, spatial skills, and reasoning (e.g., Scherer et al., 2019). However, this study also found that programming knowledge was weakly associated with benefits on literacy, including reading, writing, and listening skills, as well as overall school achievements. In view of this, it is unclear whether these studies are assessing the relationship between programming knowledge and language abilities, or that of programming knowledge and whether one is a good student.

If there are many theoretical grounds to support the parallels between programming and natural language processing, evidence has been scarcer in view of

neuroimaging studies. The first study to investigate programming comprehension using fMRI found that some regions recruited by this process are associated with functions that are also commonly involved in natural language processing (Siegmund et al., 2014). The recruitment of these functions, namely working memory, attention, and reading, could point to potential shared processes between code and natural language comprehension. However, subsequent fMRI studies that compared code and natural language comprehension have reached different conclusions. Ivanova et al. (2020) and Liu et al. (2020) both found a larger involvement of the fronto-parietal network in code comprehension. This area is sometimes referred to as the 'multiple-demand' system and is associated with domain-general cognition. Ivanova et al. (2020) also found that language regions were also activated to a small extent, but these regions may be activated automatically because of the symbols involved in code rather than indicating that language regions are involved in comprehension. Similar conclusions have been reached regarding code production. Krueger et al. (2020) found that writing prose and writing code involve quite different neural resources, namely that writing prose involves left-brain areas associated with language, whereas coding involves right brain areas associated with attention, working memory, planning, and spatial cognition. Overall, as opposed to the theoretical perspective outlined above, neuroimaging studies on code comprehension and production have yielded little reason to believe that programming and natural language processing are similar.

Other differences between programming and natural languages are that programming languages usually involve very small vocabularies (e.g., Wang, 2009), they are mostly implemented in visual form, as opposed to both aural and visual form for

natural languages (e.g., Pandža, 2016), and that they are derived by context-free grammars (e.g., Ginsburg & Rice, 1962; Jäger & Rogers, 2012; Wang, 2009), as opposed to natural languages which require more powerful grammars. However, these observations do not necessarily point to major differences in how programming and natural languages are processed since these generalizations do not reflect actual limits of the system. For example, although programming languages usually carry a small basic inventory of keywords, new items can be created as needed, up to an infinitely large vocabulary (if one has a computer with sufficient memory). Moreover, code can be pronounced, and it has been reported that reading code involves the phonological loop, a region activated during natural language reading (e.g., Hermans et al., 2018). Therefore, it is possible that the mental representation of code does not only involve visual symbolic form, but also an aural counterpart. The type of grammar that supports each system may draw a more solid line between natural and programming language processing. Although programming languages can be captured by context-free grammars (e.g., Ginsburg & Rice, 1962; Jäger & Rogers, 2012), this is not true of natural languages. Therefore, it is possible that although both programming and natural language follow grammar rules, the system supporting these rules are cognitively non-overlapping. However, it is also possible that since the grammars of natural languages are more powerful than those needed for programming languages, that the mechanisms involved with natural language processing can englobe those needed to support programming languages. Overall, although programming and natural languages are both languages, they are clearly different kinds of languages. What is striking is that many parallels persist beyond the

differences, which warrants further investigation on the underlying brain processes that support these different languages.

An often-overlooked detail in research that compares programming and natural language processing is that programming languages are necessarily always learned as non-native languages. This point is a basic premise of research on programming education (e.g., Bers, 2019; Pandža, 2016), but has mostly been omitted in research on cognition. To my knowledge, only one study has considered this aspect in comparing programming comprehension to non-native natural language comprehension (e.g., Graafsma, 2021). Although this exploratory study did not find support for shared processing mechanisms in the two, it is worth considering this point in further research on this topic. Overall, programming languages are artificial languages. In the perspective where learning an artificial language is deemed similar to learning a natural language (e.g., Grey et al., 2018; Friederici et al., 2002; Morgan-Short et al., 2012; Nation & McLaughlin, 1986; Nayak et al., 1990), learning a programming language could be like learning a natural language. In this view, knowing more than one language, no matter whether these languages are natural or artificial, is expected to confer similar effects on one's cognition.

1.4 Present Study

The present study looks at whether knowledge of more than one (artificial) language procures an advantage in learning an additional language. The first goal of the current research is to provide further experimental evidence for the claim of a multilingual advantage in language learning, more specifically in the domain grammar learning (e.g., Cox, 2017; Grey et al., 2018; Nation & McLaughlin, 1986; Nayak et al.,

1990). We expect that multilingual individuals will demonstrate a better ability to learn the rules of an artificial grammar which will be reflected in a higher accuracy on grammaticality judgements about correct and incorrect sentences in this artificial language. An additional goal is to test the claim that knowledge of a programming language is similar to that of a natural language (e.g., Fedorenko et al., 2019), more specifically, that of a second language (e.g., Graafsma, 2021; Pandža, 2016). If our hypothesis of intrinsic similarities between natural and programming languages is correct, programmers are expected to have an advantage in an artificial grammar learning task, similar to expectations placed on multilinguals.

To this end, I will compare participants' grammaticality judgement scores following familiarization to an artificial grammar, in view of their linguistic and programming experience. This experiment will test four hypotheses.

(1) The multilingual status is predicted to modulate the ability to learn an artificial grammar. If multilingualism provides an advantage in grammar learning, participants who reported knowing more than one language will achieve higher accuracy than participants who reported being fluent in only one language.

(2) The level of language dominance among multilinguals is expected to modulate the ability to learn an artificial grammar. Since the multilingual advantage in language learning is claimed to be modulated by usage, multilingual participants who are more balanced in at least two languages are expected to demonstrate the most advantage in an artificial grammar learning task among all multilinguals.

(3) The programmer status is expected to modulate the ability to learn an artificial grammar. If programming languages are processed similar to natural languages, participants who report knowing a programming language are expected to perform better than participants who do not know any programming languages, similar to the expectations placed on multilingual participants.

(4) The level of programming proficiency is expected to modulate the ability to learn an artificial grammar. As in the case of natural language, higher coding proficiency is expected to positively affect accuracy results in the grammaticality judgement task.

Previous studies have shown that artificial grammars can be learned to above-chance accuracy levels (e.g., Grey et al., 2018; Nation & McLaughlin, 1986; Nayak et al., 1990), and sentences presented in this learned grammar elicit neural activation patterns similar to those found in the case of natural language processing (e.g., Friederici et al., 2002; Morgan-Short et al., 2012). In view of the recent speculations in research on programming cognition and since programming languages are artificial languages, knowledge of a programming language may be similar to that of another natural language, more specifically a second language. In this view, knowing more than one language, either natural or artificial, is expected to confer similar effects on one's cognition.

There are three potential outcomes for each goal set in this study. First, the language status could have a significant effect on the accuracy scores such that multilingual participants perform better than monolingual participants. Second, there

could be a significant effect of the language status such that multilingual participants perform worse than monolingual participants. Third, the language status could be irrelevant to performance on this task. The same three outcomes apply for the programming status. Each of these outcomes bear different implications for theories of multilingual and programming cognition.

If multilingualism has certain effects on cognition, for example making cross-linguistic interference easier to manage or enhancing metalinguistic awareness, differences in results among monolingual and multilingual participants in our artificial grammar learning task can be attributed to an effect of these cognitive differences. For example, enhanced metalinguistic awareness could lead multilingual participants to deploy different learning strategies, perhaps be more analytic, or deploy more cognitive effort in deciphering the new grammar. In this sense, if multilingual participants perform better than monolingual participants, we can assume that it is because more involvement of the learner is beneficial in acquiring new grammatical knowledge. On the other hand, if multilingual participants perform worse than monolingual participants, we can assume that it is because this approach is detrimental to acquiring new grammatical knowledge, perhaps pointing to the scenario where grammar is best learned passively. Finally, no group differences would indicate that no matter what changes multilingualism may bring to cognition, they do not influence acquiring new grammatical knowledge.

Similarly, if programming has certain effects on cognition, such as enhancing creative thinking, metacognition, and reasoning (e.g., Scherer et al., 2019), differences in results among programmer and non-programmer participants in our artificial grammar learning task can be attributed to an effect of these cognitive differences. In this sense,

enhanced creative thinking, metacognition, and reasoning could also lead programmer participants to deploy different learning strategies than non-programmers, such that their learning is more consciously monitored. If programmers perform better than non-programmers in our task, we can assume it is because this greater involvement of the learner is beneficial to learning novel grammatical material. On the other hand, if programmers perform more poorly than non-programmers, we can once again assume it is because such learning strategies are detrimental to performance in an artificial grammar learning setting. No group difference would indicate that programming knowledge has no impact on acquiring new grammatical knowledge.

Lastly, based on these assumptions and the patterns of results obtained for the relationship between the programming and multilingualism status on achievements in our artificial grammar learning task, we can make certain inferences about the potential overlap in cognitive effects of knowing more than one natural language, or a programming language. Since there are three foreseeable outcomes for each of these relations, there are nine possible scenarios for their interactions, three in which the programming and multilingualism status have similar effects on achievements in artificial grammar learning, and six where they have dissimilar effects. The conclusion that programming and natural language knowledge may have similar effects on cognition is only warranted in the case where both the programming status and the multilingual status significantly predict the accuracy scores obtained in the grammaticality judgement task, whether it is in a positive or negative direction.

Chapter 2: Methods

2.1 Participants

Participants (*n* = 144, *M* =20.34 years, median 19 years, range 17-48 years, 58 male) were recruited either through the subject pool of the Department of Cognitive Science at Carleton University, or from the Montreal area through words of mouth. Most participants reported having a high school degree (*n* = 112). A few participants had a Cegep or College degree (*n* = 9). Finally, there were some participants with an undergraduate degree (*n* = 23).

The participants recruited through the subject pool were students registered in the introduction to cognitive science course given at Carleton University over the Winter, Summer, and Fall semesters of 2021. Students enrolled in this course are invited to participate in experiments conducted by other students in the department in exchange for course credits or a monetary compensation. For the current experiment, participants were compensated with their choice of a 2% credit on their course or a 20$ gift card from Amazon. Participants were also offered a bonus depending on their performance. Participants interested in this offer received a 1$ bonus for every block of training where they scored 75% or higher on accuracy. This bonus was also given in the form of an Amazon gift card, for a maximum of a 12$ bonus.

Although data collection produced a total of 432 files, empty (*n* = 185), incomplete (*n* = 98), or duplicated (*n* = 5) files were omitted. The major reason for the high number of empty files was a technical issue where participants were not able to move beyond the first page of the demographic questionnaire. This issue happened because the 'next' button stood outside of their browser's limit. This was easily fixed by

adjusting the browser's zoom to a 75% ratio. Instructions for how to fix this issue were presented at the very beginning of the experiment. However, to adjust the resolution, participants had to quit the experiment, then launch it again. Sometimes, participants may have relaunched the experiment multiple times before resolving the issue, giving rise to multiple empty files.

2.1.1 Monolingual vs. Multilingual Participants

The monolingual participants (*n* = 78, mean age 20.77 years, range 17-48 years, 30 male) were English native speakers either born in Canada (*n* = 69), or in a country where English is recognized as an official language (e.g., Australia, India, Ireland, Jamaica, Nigeria, Saint-Lucia, United States). The monolingual participants reported not being fluent in another language, or that they only had low levels of proficiency and use in another language. The monolingual participants who reported being fluent in another language (*n* = 12) used their first language, English, most of the time (*M* = 93.8% vs 5.4% for the second language). They were asked to rate how often they used each language either with friends, with family, at work or school, or to talk to themselves. The results revealed that for these participants, the other language was mostly used with family (*M* = 18% of the time on average), more rarely to talk to oneself (*M* = 5%), or with friends (*M* = 2%), and not at all in the context of work or school. These participants were also asked to rate their proficiency across four competencies: speaking, understanding, reading, and writing, on a scale from 1 (does not perform well at all in this competence) to 6 (performs very well in this competence). These participants all reported perfect proficiency in English, their mother tongue, as opposed to low proficiency in the other language (*M* = 1.9). A closer look at the scores revealed that their proficiency in the

other language was mostly restricted to oral competence (*M* = 2.8 for speaking, *M* = 3.7 for understanding, *M* = 0.9 for reading, *M* = 0.2 for writing). Therefore, although these participants were born in multilingual families, they did not actively engage in a multilingual lifestyle.

The multilingual participants (*n* = 66, mean age 19.81 years, range 18-30, 28 male) were, for the majority, born in Canada (*n* = 43). The rest were born in various locations, including Bangladesh (*n* = 3), India (*n* = 3), the Philippines (*n* = 2), and Syria (*n* = 2). There were no restrictions set on the number of languages, or specific languages participants knew, as long as they had native-like fluency in English. All multilingual participants either reported English as their mother tongue (*n* = 41) or learning English before the age of 10 (*M* = 3.36 years), as well as high proficiency in this language (*M* = 5.7, range 4 to 6, on a scale of 1 to 6). All multilingual participants were also fluent in at least one other language, the most popular being French (*n* = 31), Arabic (*n* = 11), Cantonese (*n* = 4), and Spanish (*n* = 3). They either rated their proficiency in this other language as intermediate (3 or above on a scale from 1 to 6) or reported using this language at least 20% of the time. Additional information on participants' first, second, and other languages known, as well as their relative dominance score in these languages is provided in Appendix 0.

More monolingual participants reported possessing an undergraduate degree (*n* = 17, 22% of this group) than multilingual participants (*n* = 6, 9% of this group). However, the two groups were similar in terms of other measures of education, such as the number of participants in their first year of undergraduate studies (*n* = 30 for monolingual participants vs. *n* = 29 for multilingual participants). These participants' demographics in

view of the multilingual status are presented in Table 1 below. The most popular majors for monolingual participants were psychology (*n* = 21), criminology or law (*n* = 11), and computer science (*n* = 9). For multilingual participants, the most popular majors were computer science (*n* = 14), commerce or business (*n* = 9), and psychology (*n* = 8). An overview of major repartition across participants based on the multilingual status is provided in Appendix A.2.

Table 1

Demographics for Monolingual and Multilingual Participants

	Monolinguals (*n* = 78)	Multilinguals (*n* = 66)
	Age	
Mean	20.8	19.8
SD	4.6	2.3
Range	17-48	18-30
	Gender	
Male	30	28
Female	48	36
Prefer not to say	0	2
	Level of education completed	
High school	53	59
College/cegep	8	1
University (undergraduate)	17	6
	Number of languages known	
Mean	1.97	3.02
SD	1.02	1.1
Range	1-5	2-7
	Dominance score (BLP)	
Mean	NA	56.66
SD	NA	39.91
Range	NA	0.82-140.31

Note. The dominance score is a measure of language dominance on a scale from 0 (completely balanced) to 218 (full dominance in one language).

2.1.2 Programmer vs. Non-Programmer Participants

Participants who reported knowing a programming language (*n* = 40, mean age = 19.3 years, range 18-26 years, 13 female) were mostly born in Canada (*n* = 27) and had English as a first language (*n* = 30), or reported high proficiency in the English language (*M* = 5.6 on a scale from 1 to 6, range 4.5-6). Non-programmer participants (*n* = 104, mean age = 20.73 years, range 17-48 years, 32 male) were also for the most part born in Canada (*n* = 85) and had English as a mother tongue (*n* = 89). The most popular programming languages known by participants were Python (*n* = 36), Java (*n* = 23), C++ (*n* = 17), C (*n* = 13), and JavaScript (*n* = 10). Additional information about the programming languages known by participants and their experience levels is provided in Appendix A.3.

Most programmer participants were in their first year of undergraduate studies (*n* = 25), and only one participant had finished their undergraduate degree. On the other hand, although many non-programmers also reported being in their first year of undergraduate studies (*n* = 34), a considerable amount of them were in their fourth year (*n* = 21) or had completed their undergraduate degree (*n* = 22). Participants' demographics in view of the programmer status are presented in Table 2. Most programmers were registered in a Computer Science major (*n* = 23), whereas the most popular majors among non-programmers were Psychology (*n* = 28), Criminology or Law (*n* = 17), and Commerce or Business (*n* = 12). The repartition of majors among participants according to the programming status is reported in Appendix A.4.

Table 2

Demographics for Non-Programmer and Programmer Participants

	Non-programmers (*n* = 104)	Programmers (*n* = 40)
	Age	
Mean	20.7	19.3
SD	4.1	2.1
Range	17-48	18-26
	Gender	
Male	32	26
Female	71	13
Prefer not to say	1	1
	Level of education completed	
High school	73	39
College/cegep	9	0
University (undergraduate)	22	1
	Number of programming languages known	
Mean	NA	3.3
SD	NA	2.01
Range	NA	1-9
	Programming experience score	
Mean	NA	2.5
SD	NA	1.09
Range	NA	1-4

2.2 Materials

2.2.1 Questionnaires

Participants' demographics, linguistic experience, and programming experience were collected through self-reported answers on various questionnaires. Demographics were collected through a questionnaire specifically designed for the purpose of this experiment. Language experience was assessed through the Bilingual Language Profile questionnaire (Birdsong et al., 2012), which is a commonly used tool to measure relative proficiency and dominance between two languages. Programming experience was

measured through a short questionnaire designed by the Language and Social Cognition Lab at Carleton University.

2.2.1.1 The Demographics Questionnaire

Our demographics questionnaire collected basic information about participants, including their age, gender, level of formal education, major, current year of study, country of birth, the number of years lived in the country of birth, the number of years lived in Canada, their native language, and other languages that they know. They were also asked whether they were fluent in another language. If they answered 'yes' to this question, they were asked to indicate which other language(s) they were fluent in. After this, participants would be directed towards further questions about their language experience. If they answered 'no' to the question on the knowledge of additional languages, the set of questions on language experience was skipped. Next, participants were asked if they knew any programming languages. Here again, if they answered 'yes', they were asked to answer additional questions about their programming experience. If they answered 'no', further questions about programming were skipped and the experiment went on to the main task instructions. All questionnaires in this experiment were set such that a participants could not proceed to the next frame without providing an answer to each required field.

2.2.1.2 The Bilingual Language Profile Questionnaire

If participants answered 'yes' to the question about whether they were fluent in another language, they were further presented with questions about their language experience. These questions were based on the Bilingual Language Profile (BLP), a tool

to measure language dominance between two languages in individuals who know more than one language (Birdsong et al., 2012). The dominance score is based on self-reported scalar responses. The same questions are answered for two languages. There are four modules to the BLP questionnaire: language history, language use, language proficiency, and language attitudes, which are weighted equally to yield a global score of 0 to a maximum of 218 points for each language. The dominance score is calculated by subtracting one language's global score from the other language's global score. The difference of these scores is a number ranging from -218 to + 218. A dominance score closer to 0 indicates a more balanced language profile in view of the two languages answered for. In the current experiment, participants were instructed to answer the questions in view of the two languages they felt the most fluent in.

There are several advantages to using the BLP. First, this questionnaire is easy to use. It is made accessible online for free, and available in different forms, either as a PDF version or a self-scoring google form and offered in a variety of languages. In the non-self-scoring version, the dominance score is easily calculated since all answers are scalar. Second, the information provided by this questionnaire is very useful for other analytic purposes. Since the dominance score is provided as a continuous measure, it allows for a fine-grained comparison of language dominance. Moreover, the different modules of this questionnaire can be considered independently to get a more detailed overview of participants' profiles. Finally, the questionnaire itself can be quickly completed, around 10 minutes, as there are no development questions. These aspects all contribute to making the BLP a useful tool to assess language dominance.

2.2.1.3 The Programming Experience Questionnaire

The programming experience questionnaire was developed by the Language and Social Cognition Lab at Carleton University and has been used in other projects involving programmers. The first question asked participants to list all programming languages they knew from the one they knew the best to the one they knew the least. Then, they had to choose which statement out of four statements described best their knowledge of programming. The statements were attributed a numerical value from one to four which represented low to high proficiency in programming. The statements were: "I have some knowledge about programming, but I would have a hard time writing a script if I had to" (1), "I have sufficient knowledge about programming and program once a month on average" (2), "I have sufficient knowledge about programming and program once a week on average" (3), and "I have sufficient knowledge about programming and program every day on average" (4). The programming experience questionnaire ended with three simple programming problems to solve. The first problem stated: "List 3 different sorting algorithms (no need to describe, just list)", the second: "Suppose you have two variables, x and y. Write code to swap their value. Use the programming language of your choice, or pseudocode", and the third: "Name a method for finding a target number in a list of sorted numbers that is faster than O(n), and what the runtime complexity of the method is". It did not matter whether participants provided accurate answers to those problems. Whether or not a participant provided an answer was used to confirm the level of experience reported in the previous frame. There are not many tools yet to assess programming experience, especially for a pool with different programming language backgrounds.

2.2.2 Stimuli

The artificial grammar learning task presented in this experiment uses a version of the artificial language Brocanto (e.g., Friederici et al., 2002; Opitz & Friederici, 2003; 2004; Opitz & Hofmann, 2015). The paradigm used for this experiment was provided by professor Opitz through personal communications. The original version of Brocanto was developed in a German context and involves diacritics, such as umlauts, which are alien to the English language. Encountering such unfamiliar symbols may place an extra cognitive load on learners, especially in view of phonological working memory, which is reported to be more developed in multilinguals (e.g., Kaushanskaya, 2012). Since the focus of this experiment is on grammar learning, it is desirable to make the task as simple as possible in view of lexical parsing. Therefore, we employ a modified version of Brocanto designed to avoid these foreseeable issues. For example, this version omits diacritics and uses alternative endings to certain lexical items in aim to make them more accessible to an English-based pool of participants. For example, the original item *rix* is changed to *ricks* in the version used here. To my knowledge, this version of Brocanto was used in one other thesis project, that of Cooper (2019). No undesirable effects related to using this version of Brocanto were reported in this study.

The artificial language Brocanto was developed according to universal linguistic principles. Its structure includes grammatical categories, such as determiners, nouns, adjectives, verbs, and adverbs. This language follows strict SVO word order. The modifiers are optional. When they are present, adjectives occur before the noun, and adverbs after the verb they modify. The determiner always precedes the noun and adjective, if there is one. Additionally, there is one special agreement rule concerning the

determiners. When immediately followed by a noun the determiner takes the form *aaf,* and when there is an intervening adjective, the form *aak*. This language was demonstrated to elicit similar neural activation as natural language (Friederici et al., 2002). Therefore, Brocanto is often said to possess ecological validity, making this artificial language a good candidate to explore principles of natural language processing in a lab setting. The lexical inventory of Brocanto is outlined in Table 3. Sentences in Brocanto are derived according to a finite-state grammar as that presented in Figure 1. This grammar generates sentences of 3 words to 8 words long.

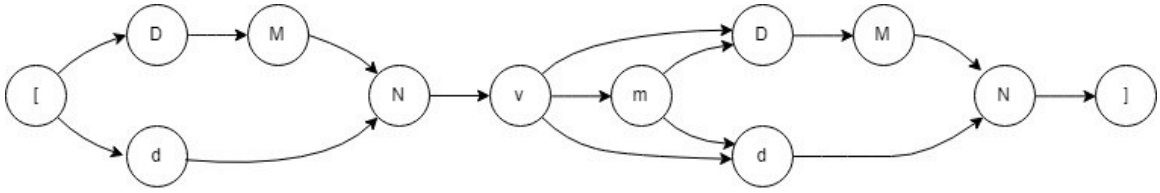
Table 3

Brocanto's Lexical Inventory by Grammatical Category

Determiners	aaf (d), aak (D)
Nouns (N)	goum, plogs, blom, troul
Verbs (v)	gleef, preel, klin, ricks
Nominal modifiers (M)	boidi, troise
Verbal modifiers (m)	nueme, rueki

Figure 1

The Grammar of Brocanto



The paradigm employed in the current experiment contains 340 grammatical sentences produced by the grammar of Brocanto. An additional 220 ungrammatical

sentences were created according to three error patterns, which are exemplified below in Table 4. One pattern involves constituent order violation at the phrase level. In these cases, a noun phrase is switched with the verbal phrase. Another error pattern involves constituent order violation at the word level. Here, a noun replaces a determiner. In the last case, the agreement rule between the determiner and the noun is violated such that the sentence involves wrong version of the determiner in view of the noun-modifier situation.

Table 4

Grammatical and Ungrammatical Sentences in the Artificial Language Brocanto

Grammatical sentence	aak troise troul ricks aaf goum
Phrase structure violation	aak troise troul *aaf goum ricks
Word order violation	aak troise troul ricks *plogs goum
Agreement violation	aaf *troise troul ricks aaf goum

Note. The point at which an element creates a violation is marked by an asterisk (*)

The resulting corpus includes a total of 560 different items. These items are organized into 12 learning blocks of 10 grammatical sentences each, 12 training blocks of 10 grammatical and 10 ungrammatical sentences each, and a testing block containing 100 grammatical sentences and 100 ungrammatical sentences. All sentences are unique and ungrammatical sentences selected in this paradigm do not have a systematic grammatical counterpart. Therefore, participants could not resort to memorization to succeed in this task. All participants were exposed to the same stimuli. The order of the blocks and items in those blocks were randomized.

2.2.3 Online Platform

The experiment's interface was built with the software PsychoPy. Following the onset of the Covid pandemic, this software has been upgraded in collaboration with the online platform Pavlovia to offer an easy way to host experiments online. The experiment can be accessed through a website link: https://run.pavlovia.org/olessia.jouravlev/agl. The entirety of the experiment, including the demographic questionnaire, the Bilingual Language Profile (BLP) questionnaire, and the programming knowledge questionnaire, was administered online through the Pavlovia platform. After signing-up for the experiment on the SONA portal, participants had access to the link that led to the Pavlovia platform. After this, the experiment could be launched at any time during the semester. However, the whole experiment had to be completed in one sitting.

2.3 Procedures

After signing up for our experiment online, participants had access to a link that led them to the online platform where the experiment was hosted (Pavlovia). Upon clicking the link, participants entered their personal identification code, after what the experiment would automatically launch in full screen. This code was used only to track participation and provide adequate compensation. Once the experiment was launched, participants were first welcomed then presented with a warning that at any moment if they were not able to proceed through the experiment, they should adjust their browser's zoom. Then, they saw a disclaimer that they could quit the experiment at any time, followed by a consent form. Participants were informed that by continuing past this point they were giving us their consent to use their data for analysis, but that no personal information would be collected.

Following these preambles, participants went through a series of questions about their demographics, language experience, and programming experience. In the case where a participant reported experience in these later two aspects, they were given additional questionnaires. After this, instructions about the main experiment were provided, and participants could launch the experiment when they felt ready. These instructions were repeated on many occasions throughout the experiment to ensure that participants knew what their task was, as well as providing time windows for participants to take breaks.

The methodology for this experiment was adapted from Opitz & Hofmann (2015). There were two main phases: a practice phase and a testing phase. During the practice phase, participants went through a series of learning blocks and training blocks. There were 12 pairs of learning and training blocks presented in a random order. Each learning block contained 10 grammatical sentences whereas each training block contained 10 grammatical sentences and 10 ungrammatical sentences. The order of sentences in each block was randomized. For learning blocks, participants were instructed to read the sentences on the screen and try to discover the rules of Brocanto. They were told that the sentences would be presented for 7 seconds and that there would be 10 sentences per block. For the training blocks, participants were told that they would now be presented with both correct and incorrect sentences in the language Brocanto and that their task on these blocks was to provide a grammatical judgement for each sentence. For each trial, participants had 7 seconds to read the sentence and provide a grammatical judgement. Participants entered their response through a keyboard key (i.e., “a” for correct and “l” for incorrect). After each trial, correctness feedback was provided and remained on the

screen for one second. Here again, participants were made aware of the time constraints and total amount of sentences, however they were not told the ratio of grammatical sentences to ungrammatical sentences per block.

To boost students' motivation, we offered them a bonus for any training block where an accuracy score equal or above 75% was reached. This bonus was 1$ per such block provided in the form of an Amazon gift card. Participants were shown their accuracy score after each training block. Moreover, throughout the practice phase, there was a tracker in the corner of the screen that indicated the participant's progression. At the beginning of each new block, whether it was learning or training, the appropriate instructions were reiterated along with an additional tracker of the progression. Participants could use these momentums to take a short break between blocks.

The testing phase contained 200 items, half of which were grammatical, and the other half ungrammatical. Again, participants were asked to provide a grammatical judgment, which they entered through pressing a keyboard key, the same as for practice. This time, participants did not receive any correctness feedback. They were told their final score and the amount of their bonus only at the end of the test block. Participants could choose to leave a comment at the end of the experiment. However, these comments were not included as part of the analysis.

In total, the experiment was estimated to take around 1h30 to complete. However, this duration could vary from one participant to another depending on whether they took breaks, or how long they took to provide an answer on training and testing blocks. The experiment was also longer in the case where the participant reported knowledge of another natural and/or programming language, in which case they had to fill in more

questionnaires before beginning the experiment. Excluding demographics and instructions, the task requires a minimum of 25 minutes, and a maximum of 65 minutes to complete. In the extremes, the whole experiment could take anywhere from 30 to 120 minutes to complete.

2.4 Analyses

A series of generalized linear models were designed to test potential interactions between performance on the grammaticality judgement task in the testing phase and relevant participants' characteristics (i.e., linguistic status, language dominance score, programming status, programming experience score). All models were fitted to the test score as a dependent variable and the fixed factors varied depending on the interaction being tested. For each model, gender and age were entered as factors of no interest that we are controlling for.

Chapter 3: Results

An overview of accuracy scores obtained on the grammaticality judgement task in the testing phase show that participants were generally successful in learning the artificial grammar (M = 63.09%, SD = 15.00). Grammatical sentences were correctly identified as such (M = 69.31%, SD = 19.78) in a larger proportion than ungrammatical sentences (M = 58.06, SD = 16.41). Among ungrammatical sentences, participants were best at identifying word order violation patterns (M = 68.26%, SD = 24.9), and worst at identifying agreement violation patterns (M = 43.37%, SD = 21.63). Additional data concerning these results are found in Appendix B.

The current study aimed to test four hypotheses. First, that multilingualism provides an advantage in an AGL task. Second, that multilinguals' dominance score

modulates their accuracy scores in AGL tasks. Third, that knowledge of a programming language provides an advantage in an AGL task. Fourth, that programmers' programming experience modulates their accuracy scores in an AGL. Our predictions were that consistent with prior research using an AGL task providing an explicit-inductive learning condition, or the instruction to identify the rules underlying the organization of the stimuli (e.g., Nayak et al., 1990), multilinguals would achieve higher grammaticality judgement accuracy scores than monolinguals. We also predicted that more balanced multilingual participants would have an additional advantage over less balanced multilingual participants, such that there would be a negative correlation between the dominance score and the grammaticality judgement accuracy score. Moreover, consistent with the literature on the potential overlap between programming and natural language cognition (e.g., Fedorenko et al., 2019; Siegmund et al., 2014), we predicted that participants who reported knowing a programming language would obtain higher accuracy measures than participants who did not know another language. As for language proficiency in multilinguals, we expected the degree of proficiency in a programming language to modulate the results such that a higher proficiency in programming would be associated with higher accuracy scores. To test these hypotheses and predictions, we ran a series of generalized linear models in RStudio (version 2021.09.0), using the *glm* function from the base R package.

3.1 First Hypothesis: No Evidence that the Multilingual Status Impacts Performance on AGL Task

The first hypothesis was that knowledge of more than one language procures an advantage in learning a new grammar. We predicted that multilingual participants would

obtain higher accuracy scores than monolingual participants on the grammaticality judgement task. To test this prediction, we created a generalized linear model with the grammaticality judgement accuracy score as the dependent variable and the multilingual status as the independent variable. Age and gender were also controlled for, but of no interest in the investigation. The formula for this model was: *Accuracy Score ~ Multilingual Status + Age + Gender*. There was not a significant difference in the accuracy scores obtained in the grammaticality judgement task by monolinguals *(M* = 63.436 %, *SD* = 14.935) and multilinguals (*M* = 62.682 %, *SD* = 15.184); $t(142) = 0.157$, $p = 0.876$). These results are summarized below in Table 5.

Table 5

Results of the Generalized Linear Model Predicting the Accuracy Score from the Multilingual Status, Age, and Gender

	Estimate	Std. error	*t*-value	*p-value*
(Intercept)	63.764	7.181	8.878	3.06e-15***
Monolingual	0.404	2.574	0.157	0.876
Age	-0.043	0.342	-0.125	0.901
GenderM	0.403	2.589	0.156	0.877
GenderNa	-13.432	10.92	-1.23	0.221

***$p < .001$

Therefore, our results do not support the hypothesis that the multilingual status influenced the grammaticality judgements scores obtained in our AGL task. There was a small, non-significant, gap between monolingual and multilingual participants in favor of the monolinguals. The other independent variables entered in the model, age, and gender, also failed to significantly predict the accuracy measures.

3.2 Second Hypothesis: Balanced Multilinguals Perform Worse on the AGL Task Than Unbalanced Multilinguals

In addition to the multilingual status, we tested whether linguistic proficiency among multilinguals had a further effect on their learning. The second hypothesis was that multilinguals' language dominance scores would modulate their grammaticality judgement accuracy scores in the AGL task. Participants with lower dominance scores were expected to obtain higher accuracy scores than less balanced multilinguals. The generalized linear model created to test this prediction was fitted with the grammaticality judgement score as the dependent variable, the dominance score obtained from the BLP questionnaire as the independent variable, and age and gender as additional independent variables of no interest (formula = *AccuracyScore ~ BLP +Age +Gender*). The results of this model uncovered a significant effect of the dominance scores on the accuracy scores obtained in the grammaticality judgment task ($t(142) = 2.275$, $p = 0.026$). The summary of the model's results is shown in Table 6 and the relationship between the language dominance (BLP) scores and the grammaticality judgement accuracy scores is illustrated in the scatter plot in Figure 2.

Our results support the hypothesis that the language dominance score modulated the grammaticality judgement accuracy scores obtained in an AGL task. However, the direction of this effect goes against our prediction. Whereas we expected that more balanced multilingualism would be associated with better results on this task, it was less balanced multilinguals who generally obtained higher accuracy scores. Age and gender were non-significant predictor of the accuracy score.

Table 6

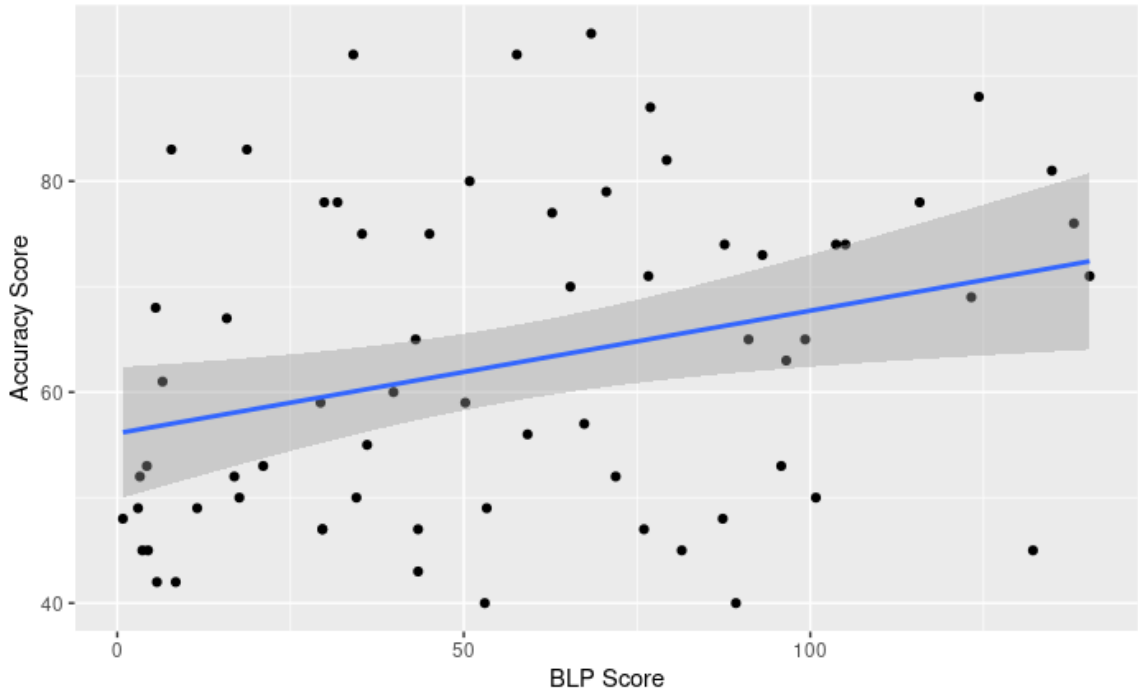
Results of the Generalized Linear Model Predicting the Accuracy Score from the BLP Score, Age, and Gender

	Estimate	Std. error	*t*-value	*p-value*
(Intercept)	64.524	16.845	3.830	3.04547e-4***
BLP	0.107	0.047	2.275	0.026*
Age	-0.425	0.801	-0.531	0.597
GenderM	1.912	3.731	0.512	0.61
GenderNa	-9.224	10.864	-0.849	0.399

*$p < .05$. ***$p < .001$

Figure 2

Scatter Plot of the Variance in Accuracy Scores According to the BLP Score



3.3 Third Hypothesis: Strong Evidence that Programmers Outperform Non-Programmers in the AGL Task

The third hypothesis was that knowledge of a programming language would procure an advantage in learning a new grammar. We predicted that programmer participants would obtain higher accuracy scores than non-programmer participants on the grammaticality judgement task. To test this prediction, we created a generalized linear model with the grammaticality judgement accuracy score as the dependent variable and the programmer status as the independent variable. The multilingual status, age, and gender were included as additional independent variables. The formula for this model was: *Accuracy Score ~ Programmer Status + Age + Gender + Multilingual Status*. There was a significant difference in the accuracy scores obtained in the grammaticality judgement task by programmers *(M* = 67.65 %, *SD* = 15.08) and non-programmers (*M* = 61.34%, *SD* = 14.67; $t(142) = 2.493$, $p = 0.014$). These results are summarized below in Table 7.

Table 7

Results of the Generalized Linear Model Predicting the Accuracy Score from the Programmer Status, Age, Gender, and the Multilingual Status

	Estimate	Std. error	*t*-value	*p-value*
(Intercept)	59.619	7.244	8.23	1.26E-13***
Programmer	7.428	2.979	2.493	0.014 *
Age	0.084	0.34	0.246	0.806
GenderM	-1.688	2.676	-0.631	0.529
GenderNa	-15.465	10.752	-1.438	0.153
Monolingual	1.109	2.543	0.436	0.663

*$p < .05$. ***$p < .001$

Therefore, our results support the hypothesis that knowledge of a programming language procures an advantage in an AGL task. Programmers obtained higher accuracy scores than non-programmers indicating that knowledge of a programming language is associated with a beneficial impact on performance in this task.

3.4 Fourth Hypothesis: No Evidence that Programming Proficiency Impacts Performance in the AGL Task

The last hypothesis was that programming experience would further modulate the accuracy scores obtained by programmers in the AGL task. We predicted that programmer participants who reported a higher level of programming experience would achieve higher grammaticality judgement accuracy scores than participants who reported a lower level of programming experience. To test this, we created a generalized linear model fitted to the accuracy score as a dependent variable with the programming experience level as an independent variable, as well as age, gender, and the multilingual status as additional independent factors (formula = *Accuracy Score ~ Programming Experience + Age + Gender + Multilingual Status*). The result of this analysis was not significant ($p = 0.57$). The summary of the model's results is shown in Table 8.

This analysis did not capture a significant effect of the programming experience level on the grammaticality judgement accuracy scores obtained on the AGL task. Therefore, the hypothesis that the level of programming experience has a further influence on programmers' accuracy scores is not supported.

Table 8

Results of the Generalized Linear Model Predicting the Accuracy Score from the Programming Experience Level, Age, Gender, and the Multilingual Status

	Estimate	Std. error	*t*-value	*p-value*
(Intercept)	71.783	27.472	2.613	0.013*
ProgExp	-1.401	2.459	-0.57	0.573
Age	0.175	1.278	0.137	0.892
GenderM	-3.693	5.324	-0.694	0.493
GenderNa	-18.905	16.465	-1.148	0.259
Monolingual	-2.67	5.111	-0.522	0.605

*$p < .05$.

3.5 Exploratory Analysis of a Potential Interaction Between the Programming and the Multilingualism Status

Finally, an additional analysis was performed post-hoc to explore the potential interaction between the multilingualism status and programming status. Since this analysis was exploratory, we did not have any prediction in view of the outcome. To test this interaction, we ran a generalized linear model following the formula *Accuracy score ~ Programming status * Multilingual status + Age + Gender*. The results of this analysis show that the effect of the programming status remains significant ($p = 0.013$) beyond potential interactions with multilingualism. Therefore, programmers generally performed better in our task than non-programmers, regardless of these participants' language profile.

Table 9

Results of the Generalized Linear Model Predicting the Accuracy Score from the Interaction of the Multilingualism and Programming Status, Age, and Gender

	Estimate	Std. Error	*t*-value	*p-value*
(Intercept)	59.072	7.266	8.129	2.287e-13***
Programmer	10.015	3.973	2.52	0.013*
Monolingual	2.65	2.99	0.887	0.376
Age	0.067	0.34	0.197	0.844
GenderM	-1.718	2.677	-0.642	0.522
GenderNA	-15.888	10.762	-1.476	0.142
Programmer:Monolingual	-5.516	5.606	-0.984	0.327

*$p < .05$. ***$p < .001$

Chapter 4: Discussion

There were two main goals to this study. The first goal was to test the claim that knowledge of another language provides an advantage in learning a foreign language (e.g., Cenoz, 2013; Hirosh & Degani, 2018; Montanari, 2019). More precisely, the focus was placed on the domain of grammar learning, which is an area that has been understudied in view of a potential multilingual advantage. There have been few studies on this topic to this day (e.g., Cox, 2017; Grey et al., 2018; Nation & McLaughlin, 1986; Nayak et al., 1990), and their results have been mixed and hard to compare because of methodological differences. The current research project replicated the only task condition among those studies which, to our knowledge, yielded positive results for a multilingual advantage in grammar learning, namely the rule-discovery artificial grammar learning task from Nayak et al. (1990). One innovation of the present study was the inclusion of a larger pool of participants (n = 144) than that of Nayak et al. (n = 48).

Another innovation was the use of an artificial language that bears more parallels to a natural language than the one used in the original study. This artificial language, Brocanto, follows grammatical rules that are attested in natural languages of the world and has been demonstrated to have the power to elicit brain activation patterns similar to those found in the case of natural language processing (e.g., Friederici et al., 2002; Morgan-Short et al., 2012). Although results in studies using traditional artificial grammar paradigms have demonstrated that participants can learn the rules underlying these systems, neuroimaging research indicates that artificial grammars led to different ERP patterns than natural language grammars. This was stated by Friederici et al. (2002) as a main interest in designing Brocanto. One other study that looked at the question of the multilingual advantage in grammar learning also used a version of Brocanto (Grey et al., 2018). However, their results are not comparable to those obtained by Nayak et al. (1990) since the more recent study includes an instructed explicit-deductive learning condition, where participants were given a grammar lesson of the target language rather than be directed towards finding these rules on their own, as in an explicit-inductive learning task.

To summarize, the first goal of the current study was to revisit the claim for a multilingual advantage in language learning, more specifically in view of grammar learning, and fill certain methodological gaps in this literature by replicating an explicit-inductive rule-discovery learning condition using an ecologically valid artificial language as the target language of our grammar learning task. We tested the hypothesis that multilingualism led to higher accuracy scores in an AGL task as well as the hypothesis that more balanced multilingualism would procure a further advantage in this task.

The second goal of our research was to test the claim that programming and natural languages are processed similarly. Consistent with recent literature (Graafsma, 2021), we adopted the premise that knowledge of a programming language is similar to that of a non-native language. In view of language learning, this premise implies that knowledge of a programming language would provide benefits like that of another language. We hypothesized that participants with knowledge of a programming language would reach higher accuracy scores in the artificial grammar learning task than participants without such experience and that programmers who reported higher levels of programming experience would demonstrate an additional advantage in this task.

Our results failed to replicate those obtained by Nayak et al. (1990) in view of the multilingual advantage in language learning providing explicit-inductive, or rule-discovery, task instructions. The multilingual and monolingual participants in our study obtained similar accuracy scores on the grammaticality judgement task following exposure to an artificial language. We also failed to find an advantage for more balanced multilinguals in this task. In fact, the results went in a direction opposite to our prediction. Less balanced multilinguals who had a dominance in one language generally performed better than more balanced multilinguals. Overall, these results indicate that multilingualism do not procure cognitive abilities changes that have an effect, either positive or negative, on the outcome of artificial grammar learning.

One potential explanation why our study failed to capture a significant difference in performance among monolingual and multilingual participants is that the linguistic status was self-reported, and thus, subject to each's personal interpretation of fluency. On the one hand, some participants reported being fluent in another language, but with very

low levels of use. On the other hand, many participants who reported being monolingual then indicated that they had some knowledge of another language (n = 47). In view of this, it is possible that the language status reported in our data did not provide a strong enough distinction among participants. Unfortunately, a deeper examination of language experience was only administered in the case where the participant indicated being fluent in another language. Therefore, we do not have a measure of the extent of monolingual participants' knowledge in these additional languages.

Another possible explanation for why our results did not support the claim for a multilingual advantage in language learning is the lack of a meaning mapping in the artificial grammar paradigm. This aspect has been criticized by others (e.g., Grey et al., 2018) as semantics is considered to play an important role in grammar learning. Although the artificial grammar we used is based on rules attested in natural languages, the lack of a semantic component may have kept the stimuli from eliciting mental processes like those involved in cases of natural language learning. Moreover, if a semantic component is necessary to trigger language abilities, it is possible that our results reflect the implication of other, non-linguistic skills. The validity of AGL paradigms in experimental investigations of natural language processing has been debated (e.g., Ettlinger et al. 2016; Dekeyser, 2003; Robinson, 2010). One important criticism of these tasks is that one may succeed in them by formulating generalizations about the linear sequencing of items, and how they pair with each other, rather than by learning a grammar, or figuring out a hierarchical organization of the elements (Dekeyser, 2003). In this view, above-chance accuracy in these tasks may be achieved through identifying landmarks in the stimuli' surface characteristics. For example, a learner may notice that a

certain class of elements always precede another class of elements, in which case their answer to whether the stimuli is correct or incorrect will depend solely on this kind of linear association, and not on the internalization of a grammar.

Alternatively, the multilingual advantage in language learning may not only be promoted by differences in cognitive abilities, but perhaps has its roots in social grounds. As mentioned earlier, multilingual learners may benefit in learning new languages through support from a multilingual community (e.g., Clyne et al., 2004), or through practicing with peers (e.g., Dmitrenko, 2017). These aspects being exempt from laboratory setting may be the reason why attempts to identify a multilingual advantage in grammar learning withing these settings have so far been inconclusive.

To explain why the results of the second analysis failed to meet our expectations, we took a closer look at the linguistic profiles of multilingual participants in our study. Our participants had varied levels of language dominance score, which was good within the perspective of testing the relationship between performance on artificial grammar learning and the degree of language dominance. However, we had not foreseen that language dominance among participants may be tied to other factors. We noticed a tendency for reported measures of language use to differ according to the mother tongue. Multilingual participants whose mother tongue was English used this language on average most of the time (M = 81.37%), whereas language use was more equally divided for non-native English multilingual participants (M = 41.6% for the mother tongue vs. 54.72% for English vs. 3.78% for other languages). Language use habits were reflected in average dominance scores, such that participants whose first language was English generally obtained higher dominance score on the BLP questionnaire (n = 41, M = 73.16)

than multilingual participants who reported another language as a mother tongue (n = 25, M = 29.6). This indicates that, on average, multilingual participants whose mother tongue was English were less balanced than those whose mother tongue was not English. In this view, the tendency captured by the analysis of the effect of language dominance on performance in our grammar learning task may have reflected an effect of the mother tongue rather than the dominance score. A look at the accuracy scores obtained on the grammaticality judgement task according to the mother tongue show a small trend in favor of participants whose mother tongue was English (M = 64% vs. M = 58.68% for non-native English participants). Our prediction was that a lower dominance score would be associated with a higher grammaticality judgement accuracy score in the AGL task. However, the dominance scores in our data set may have been correlated with confounding characteristics of the learners

One reason why the mother tongue would have such an influence on the results may have to do with the nature of the artificial language used in the experiment. As mentioned earlier, one strength of Brocanto is that it has ecological validity, or, in other words, it is based on rules and principles attested in the natural languages of the world. This characteristic makes Brocanto well-suited for generalizations about natural language processing. However, one downfall of this aspect is that it does not allow to fully rule-out the possibility for prior linguistic knowledge to interfere with learning, unless there is a very strict control of participants' linguistic background. Two out of the three error patterns involved in the grammaticality judgement task revolved around aspects of word order. In this perspective, it is possible that multilingual participants whose native language does not involve strict word order, such as Arabic (n = 7), or Tagalog (n = 2),

had a harder time noticing these patterns. If this explanation is true, the fact that all monolingual participants were native English speakers surely contributed to attenuate the gap between the two groups. Similarly, the fact that native-English multilingual participants reported on average higher dominance scores certainly fogged the effect of the dominance scores on the grammaticality judgement accuracy scores. A post-hoc analysis showed that whether a multilingual participant's native language was English had a nearly significant effect ($p = 0.099$) in predicting the accuracy score on the grammaticality judgement task. Moreover, this explanation is consistent with our finding that, generally, accuracy in identifying ungrammatical sentences as such was greater on items that presented a phrase structure or word order violation, than on those presenting an agreement violation.

An alternative explanation is that English proficiency itself modulated performance in grammar learning. Competence in the language of instruction has been claimed to have an influence on the manifestation of a multilingual advantage in language learning (e.g., Edele et al., 2018; Sanz, 2000; Swain et al., 1990). For example, Edele et al. (2018) found that only balanced multilinguals who had high levels of proficiency in the language of instruction, their L2, outperformed their monolingual peers. Although non-native English multilingual participants in our study all reported above intermediate levels of proficiency in this language, it is possible native-like proficiency in the language of instruction is required for the multilingual advantage to emerge. Therefore, the heterogeneity of the multilingual group may have hindered the potential of our study to uncover a multilingual advantage in our task and diminish the influence of language dominance on performance in AGL.

For the programmer status, our results did show a significant positive effect of programming knowledge on these accuracy measures, but there was no additional effect of programming experience. An exploratory analysis performed post-hoc confirmed that this effect was not due to an interaction with the multilingualism status. According to our assumptions cited earlier in section 1.4, these results may indicate that programming knowledge procures certain cognitive abilities that are beneficial in an artificial grammar learning task. Since the effect of the programmer status differs from that of the multilingual status, we cannot conclude that this advantage has anything to do with a potential underlying cognitive overlap between programming and natural language processing.

The discrepancy between the effect of multilingualism and programming knowledge indicates that our task may have tapped into skills that are enhanced by programming expertise but have less or little to do with multilingualism. In this view, our study brings into question the need to reconsider some fundamental aspects in using artificial grammar learning paradigms to study aspects of natural language acquisition in a laboratory setting. Success on explicit-inductive artificial grammar learning tasks may depend in larger part on inductive reasoning abilities than on language abilities (e.g., Martinez et al., 2019). Formulating rules about the sequencing of elements can resemble formulating algorithms, something programmers have more practice with than non-programmers. Programming expertise is associated with better performance on figural inductive reasoning tasks (e.g., Helmlinger et al., 2020), which depends on pattern recognition skills and algorithmic thinking. Therefore, it is possible that our experiment measured group differences with regards to inductive reasoning abilities rather than

language learning abilities. This would explain why programmers, but not multilinguals, demonstrated an advantage in this task. This explanation is consistent with the findings of our exploratory analysis showing that the programming status remained a significant predictor of better achievements in our artificial grammar learning task beyond potential interactions with the multilingualism status.

Finally, our analysis of the effect of the programming experience score on the accuracy scores in the AGL task did not yield a significant interaction between the two. The most likely explanation is that our programming experience question was not sensitive enough to distinctions in programming habits among participants. For this measure to be more suited to the analysis, it should have captured a distinction between participants who used a programming language on a daily basis versus those who used code only once in a while. However, our questionnaire only provided a general measure of usage and proficiency grouped together. Therefore, separate questionnaire items to measure usage and proficiency would be informative for future research interested in measuring levels of programming expertise. Additionally, an indication of the context of programming and whether their programming knowledge was self-taught or acquired through courses could also inform researchers on participants' programming profile.

Chapter 5: Conclusion

Our study found evidence that knowledge of a programming language, but not that of additional natural languages, was associated with better scores on an artificial grammar learning task involving rule-discovery, or explicit-inductive learning. In each case, results for the influence of proficiency on performance in this task went against our predictions. Whereas programming experience had no significant influence on

performance, results showed that a higher level of language dominance among multilinguals significantly predicted higher accuracy scores in the AGL task. It is unclear whether the effect of language dominance among multilingual learners was fogged by confounding variables such as the mother tongue, or the level of proficiency in the language of instruction. This pattern of results indicates that success in our task may have more importantly been modulated by unforeseen factors, such as inductive reasoning abilities, rather than language learning abilities. Overall, we did not find evidence in support of the claim for a multilingual advantage in language learning, nor for the claim that knowledge of a programming language resembles that of a natural language in cognition. In the perspective of natural language learning, our results contribute to a better understanding of the factors influencing success in AGL tasks. In the perspective of programming cognition, we uncovered that programming knowledge has potential benefits for explicit-inductive learning of an artificial grammar.

Appendices

Appendix A

Additional Demographic Information

Table A.1

BLP Score and Languages Known Among Participants

Subj.	BLP	L1	L2	3rd	4th	5th	6th	7th
1	17.62	Arabic	English	French				
2	3.63	Arabic	English					
3	53.03	Nepali	English	Hindi	Japanese	French		
4	95.81	English	French	Spanish				
5	36.05	English	Portuguese	French	Spanish			
6	134.86	English	French					
7	89.27	English	French	Spanish	Japanese	Arabic		
8	124.32	English	French					
9	8.44	Arabic	English	French				
10	5.54	Bengali	English	Urdu	Hindi			
11	3.00	Cantonese	English	Mandarin				
12	76.01	Cantonese	English	French	Spanish	Mandarin	Korean	Japanese
13	87.37	English	French					
14	29.88	French	English	Spanish	Japanese	Serbian		
15	35.33	English	Russian	French				
16	138.04	English	French					
17	67.39	English	French	English	French			
18	31.79	Bangla	English	Hindi	Urdu			
19	65.39	English	French	Arabic				
20	103.71	English	French					
21	96.53	English	Persian	French				
22	59.21	English	Arabic	Korean				
23	50.85	Cantonese	English	French				
24	87.64	English	French	Arabic	Italian			
25	105.07	English	French	Spanish				
26	79.28	English	Somali					
27	7.82	English	Arabic	French				
28	70.57	English	French	Spanish				
29	68.39	Marathi	English	Hindi	German	Korean		

30	11.53	English	French				
31	0.82	Spanish	English	Filipino			
32	34.06	English	French	Spanish			
33	29.61	Arabic	English				
34	62.75	English	Spanish	French			
35	5.73	Arabic	English	Spanish			
36	16.90	Swahili	English	Lingala			
37	53.31	English	French				
38	71.92	English	Arabic				
39	115.79	English	French				
40	43.41	Tagalog	English				
41	15.80	Tagalog	English	Spanish			
42	43.41	Mandarin	English				
43	99.26	English	French				
44	3.27	English	French				
45	21.06	Gujarati	English	Hindi	Arabic	French	
46	45.05	English	French				
47	81.46	English	Arabic				
48	4.45	Arabic	English	French			
49	91.09	English	Telugu	English	Telugu		
50	140.31	English	French	English	French		
51	43.05	Cantonese	English	French			
52	18.71	French	English				
53	132.13	English	French	Swahili			
54	50.22	Bangla	English	Spanish	French		
55	123.23	English	French	Mandarin			
56	76.64	English	French	Mandarin			
57	29.61	English	Gujarati	Hindi	Marathi	French	
58	57.66	Arabic	English	Spanish	German	Japanese	Turkish
59	100.81	English	French				
60	76.93	English	French	Cantonese	Mandarin		
61	34.51	English	French	Spanish			
62	4.27	English	French				
63	93.09	English	French	Spanish			
64	6.54	Italian	English	Spanish	French		
65	39.86	French	English				
66	29.33	English	French				

Note. BLP = Bilingual Language Profile score, a measure of language dominance. A score closer to 0 indicates a more balanced language profile.

Table A.2

Distribution of Participants' Majors Based on the Multilingual Status

Major	Monolinguals (*n* = 78)	Multilinguals (*n* = 66)
Accounting	3	6
Biology	1	1
Biotechnology and/or biochemistry	1	2
Cognitive science	5	2
Commerce and/or business	5	9
Communication	1	0
Computer science	9	14
Criminology and/or law	11	6
Design	0	1
Engineering	1	0
English	1	0
Finance and/or economics	2	1
Global development	1	0
Health science	0	3
History	2	0
Linguistics	1	0
Mathematics and/or physics	1	2
Neuroscience	2	1
Philosophy	0	1
Political science	1	1
Psychology and/or social work	21	8
N/A	9	8

Table A.3

Programming Languages Known and Levels of Programming Experience Among Programmer Participants

Subj.	1st	2nd	3rd	4th	5th	6th	7th	8th	9th	Exp.
1	Java	Python	C++							2
2	SmallBasic	C++								1
3	C	Python	Java							4
4	Python	Java	C							1
5	Python	Turing	Java							3
6	Python									1

7	Python								3
8	Python								2
9	Java	Python							1
10	Python	Java							4
11	Python	HTML	MatLab	Java	R				1
12	JavaScript	Python	C++						2
13	C	C++	Python	HTML	CSS	JavaScript	Java		2
14	Python	Java	C						3
15	JavaScript	TypeScript	react	C++	C	Java	Python	Rails Ruby	4
16	JavaScript	C++	C	Ruby	Java	Python			4
17	Java	C++	Python	SQL	JavaScript	C#			2
18	Python	Java							4
19	C++	Python							3
20	Vivado 2016	MatLab	C++	C	Java	RSlogix5	Composer		2
21	C	C++	Python						3
22	Python	Java	C++	HTML					4
23	Java	Python	JavaScript	HTML	CSS				2
24	C++	JavaScript	TypeScript	Python	SQL				4
25	C	PHP	HTML	SQL	JavaScript	Swift	Python	Java	3
26	Java	Python	C++						3
27	Python	JavaScript	Java						2
28	Python	SQL							3
29	C								3
30	Visual Basic	Python							1
31	C	Python							1
32	Java	C#	Python	C++					3
33	C++	Python							3
34	C#	C++	Python	Java	JavaScript				4
35	C++	Java							1
36	Python	C							3
37	Python	Java	C						3
38	Visual Basic								1
39	Python								3
40	Python	Stata							1

Table A.4

Distribution of Participants' Majors Based on the Programming Status

Major	Non-Programmers (*n* = 104)	Programmers (*n* = 40)
Accounting	9	0
Biology	2	0
Biotechnology and/or biochemistry	2	1
Cognitive science	4	3
Commerce and/or business	12	2
Communication	1	0
Computer science	0	23
Criminology and/or law	17	0
Design	0	1
Engineering	0	1
English	1	0
Finance and/or economics	2	1
Global development	1	0
Health science	3	0
History	2	0
Linguistics	1	0
Mathematics and/or physics	1	2
Neuroscience	3	0
Philosophy	1	0
Political science	2	0
Psychology and/or social work	28	1
N/A	5	12

Appendix B

Grammaticality Judgements Accuracy by Stimuli Type

Grammatical sentences (%)		Ungrammatical sentences (%)					
M	SD	*M*		SD			
69.31	19.78	58.06		16.41			
		PV (%)		WV (%)		AV (%)	
		M	SD	*M*	SD	*M*	SD
		62.25	25.3	68.26	24.90	43.37	21.63

Note. PV = Phrase structure violation, WV = Word order violation, AV = Agreement violation

Appendix C

Additional Information on Group Distribution

	Monolinguals (*n* = 78)		Multilinguals (*n* = 66)	
	Non-prog. (*n* = 61)	Programmers (*n* = 17)	Non-prog. (*n* = 43)	Programmers (*n* = 23)
	Age			
Mean	21.15	19.41	20.14	19.22
SD	4.98	2.27	2.46	1.95
Range	17-48	18-25	18-30	18-26
	Gender			
Male	19	11	13	15
Female	42	6	29	7
Prefer not to say	0	0	1	1
	Level of education completed			
High school	36	17	37	22
College/cegep	8	0	1	0
University (undergraduate)	17	0	5	1
	Test score accuracy (%)			
Mean	62.61	66.41	59.53	68.57
SD	15.12	14.27	13.98	15.90
	Accuracy identifying grammatical sentences (%)			
Mean	67.97	70.18	65.53	79.26
SD	19.42	20.01	20.14	17.70
	Accuracy identifying ungrammatical sentences (%)			
Mean	58.56	63.76	54.72	58.78
SD	16.93	14.61	13.53	20.41
	Accuracy on phrase structure violations (%)			
Mean	59.91	72.01	59.83	65.74
SD	24.87	24.63	22.89	30.32

	Accuracy on word order violations (%)			
Mean	67.41	77.68	63.89	71.74
SD	25.44	17.09	22.43	31.15
	Accuracy on agreement violations (%)			
Mean	48.09	41.18	40.17	38.47
SD	19.7	21.27	20.55	27.14

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